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Customers and Markets: Both are Essential to Credit-Risk Measurement in Australian Banks

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Customers and Markets: Both Are Essential to Credit-Risk Measurement in Australian Banks

David E. Allen, [1]Robert Powell

ABSTRACT

This paper compares credit models that incorporate a market component to those that are solely-customer based. We found that customer-only models understated credit risk during the Global Financial Crisis (GFC) and do not adequately differentiate between industries. Models that focus too heavily on the market can overstate credit risk in times of high volatility. We recommend a two-factor modelling approach that incorporates both customer and market risk to improve the accuracy of credit-risk measurement as well as assist lenders with early risk detection.

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JEL Classification: M00, N20.

1. INTRODUCTION

The Global Financial Crisis (GFC) has highlighted the importance of understanding credit risk in extreme situations. In particular, it has raised widespread concern about the ability of banks to accurately measure and provide for credit risk.

For lenders, measuring credit risk is essential, not only in avoiding bad debts, but also in many other respects, including making provisions, setting discretionary authorities for credit officers, pricing for risk, setting policies and procedures, maintaining capital adequacy and

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detecting deteriorating assets at an early stage. For regulators, it is critical in ensuring prudent lending standards and adequate capital.

Given the indispensability of accurate credit information, banks and regulators face a major issue: how to choose between the several available credit-modelling techniques, each of which assess a wide range of different criteria but may produce conflicting outcomes. We maintain that, in essence, each of these criteria relates to one of two factors – the customer or the market – but that each credit model places a different degree of emphasis on them.

Models that are predominantly customer-based (that is, concerned with the creditworthiness of the borrower) usually involve an assessment of the borrowing firm's financial position, management and credit history. It is important to understand that most of these models are designed to measure credit risk under 'normal' or static conditions and do not take into account fluctuations in market values of assets. There are several well-known examples in this category, five of which are provided here, each with variations in the way they measure customer risk. First, the z score developed by Altman (1968; revisited 2000) uses five balance-sheet ratios to predict bankruptcy. Second, Moody's KMV Company (2003) RiskCalc model is based on 11 financial measures and provides an estimated default frequency (EDF) for private firms. Third, ratings agencies provide credit ratings based on customer creditworthiness. Some of these ratings do incorporate an assessment of industry and economic conditions, but they are made at a specific point in time and are not designed to ratchet up or down with fluctuations in the business cycle. Fourth, CreditMetrics (Gupton, Finger & Bhatia 1997) incorporate credit ratings into a transition matrix that measures the probability of transitioning from one rating to another, including the probability of default. Fifth, the Basel Accord standardised approach measures corporate credit risk for capital adequacy by applying risk weightings on the basis of customers' external credit rating.

Other models provide a greater focus on market or industry risk than on customer creditworthiness; four examples are provided here. First, the Merton/KMV model (Crosbie & Bohn 2003; Merton 1974) uses a combination of the structure of the customer's balance sheet and fluctuations in the market value of assets to calculate default probabilities. Second, CreditPortfolioView (Wilson 1998) uses a similar transition methodology to CreditMetrics, but adjusts the transition probability to allow for an industry component derived through macroeconomic analysis. Third, *i*Transition (Allen & Powell 2009b) uses a transition matrix that incorporates an industry risk factor derived from equity-price fluctuations. Fourth, Jarrow (2001) includes equity prices in the estimation of default probabilities.

Understanding the interaction between market and credit risk is sufficiently important that the Bank for International Settlements (BIS) set up a task force to examine the link between the two. The BIS (2009) task force reported that market and credit risk are driven by the same underlying forces, which interact significantly in determining asset values, and that default may be affected by fluctuations in these asset values. Similarly, the Bank of England (2008) makes the point that not only do asset values fall in times of uncertainty, but rising probabilities of default make it more likely that assets will have to be liquidated at market values.

Thus, this study addresses the question of whether different economic circumstances create differences in outcomes between customer-based credit models and market-based credit models. Using an Australian setting, this study compares credit risk before and after the onset of the GFC using four different credit-risk models: two that incorporate both customer and market measurements (but each to a different degree), and two that are predominantly customer-based.

The two customer models are the CreditMetrics transition-matrix approach, which we term the 'undiversified transition model', and the Basel Accord standardised approach of calculating credit risk on a risk-weighted asset basis, which we term the 'Basel model'. The two models that include market parameters are the Merton/KMV structural model, which we term the 'structural model', and the *i*Transition approach of Allen and Powell, which we term the '*i*Transition model'.

To ensure a thorough examination of the models across a range of circumstances, we not only examine the models in different cycles, but also incorporate measures of different risk extremes within each cycle and apply the measures across a range of industries. These measures (explained below) include value at risk (VaR), conditional value at risk (CVaR), probability of default (PD) and conditional probability of default (CPD).

The next section outlines contributions and benefits of the study; sections on risk measurements, data and methodology, results and conclusions follow.

2. STUDY SETTING, CONTRIBUTION AND BENEFITS

The study is set in an Australian context because the Australian banking industry is considered to have fared far better than its global counterparts over the GFC, and is deemed to have among the safest banks in the world (the four major Australian banks are among the only eight global banks with AA ratings). The Reserve Bank of Australia (RBA 2009a) reports, "The Australian financial system has, throughout the crisis period, remained resilient. In aggregate, the Australian banks have experienced only a modest decline in profitability. While there has been some diversity of performance across banks, increases in loan losses and impairments across the banking system to date have been lower than in many other countries". In 2008, US banks posted a collective loss of \$12 billion, and the five largest UK banks a collective loss of £20 billion. In contrast, Australian banks showed profits of \$18 billion. Whilst impaired assets approximately trebled in Australia, the US and the UK over the two years to March 2009, the magnitude of Australian impaired losses (0.95 per cent of total assets) was much lower than the US (8.8 per cent) and the UK (6.6 per cent) (Bank of England 2009; Federal Reserve Bank 2009; Reserve Bank of Australia 2009b). Among the RBA's reasons why Australian banks fared better than other banks were a lower exposure to risky securities such as sub-prime residential mortgage backed securities, lending standards that were not eased to the same degree as elsewhere, and the regulatory environment (particularly the Australian Uniform Consumer Credit Code), which places a strong obligation on banks to make responsible decisions (Reserve Bank of Australia 2009a). Overall, Australian banks are perceived as having fared much better during the GFC than other global banks, in large part because of the lower credit (default) risk in their underlying assets. Against this background, we examine the credit risk faced by Australian banks, with the study showing that different models (having varying weightings for customers and markets) perceive this credit risk very differently.

During the GFC, many global banks were not adequately prepared to deal with the extent of defaults and increased impaired assets, and were left scrambling for capital and funding just when it was most difficult to obtain. This study examines credit risk before and during the GFC in the Australian setting, using a variety of customer- and market-based models. The study is intended to provide a number of benefits to banks. First, by comparing these models' risk measurements to actual changes in impaired assets, the study shows the inherent shortfalls of models that are biased towards either customers or markets. The study highlights the importance of having a two-factor (customer and market) approach to credit-risk measurement, which in turn can help banks determine provision and capital needs.

Second, and related to the previous point, this study aims to help banks gain a greater understanding of the market-based component of credit risk; this will, in turn, help them determine what capital buffers might be required for downturns. Whilst capital requirements are stipulated by regulators (on the basis of the Basel Accords), banks also need to manage their own capital needs, which may be above the regulatory minimum. According to the International Monetary Fund, the Basel system "does emphasise that banks should address volatility in their capital allocation and define strategic plans for raising capital that take into account their needs, especially in a stressful economic environment". As measured by a market approach (such as the structural model), capital decreases during a downturn due to declining market-based asset values; under these circumstances, as pointed out by the Bank of England (2008), a mark-to-market approach provides a measure of how much capital needs to be raised to restore confidence in a bank's market capitalisation.

Third, the study includes unique modelling techniques, which incorporate CVaR and market-based industry factors (the *i*Transition model) into credit modelling. These were developed by the authors using pre-GFC data (Allen & Powell 2009a, 2009b), and this study examines the performance of these metrics during the GFC. The CVaR techniques help banks better understand and measure credit risk in extreme circumstances, such as those experienced during the GFC. The *i*Transition model, which incorporates both customers and markets, can (as shown in this study) provide banks with a more balanced approach to credit-risk measurement than the solely customer-based models (which we show can underestimate credit risk in extreme circumstances) and solely market-based models (which we show can overestimate credit risk in extreme circumstances).

3. VALUE AT RISK (VAR) AND PROBABILITY OF DEFAULT (PD)

VaR is a well-understood and widely used metric for measuring market risk; it has become increasingly popular for measuring credit risk. VaR measures potential losses over a specific period within a given confidence level. Credit models that incorporate VaR include CreditMetrics (Gupton et al. 1997), CreditPortfolioView (Wilson 1998), and *i*Transition (Allen & Powell 2009b). However, the use of VaR has been criticised by Artzner, Delbaen, Eber and Heath (1997; 1999), as it does not satisfy mathematical properties such as subadditivity. Perhaps the biggest shortfall of VaR is that it excludes losses beyond VaR. Therefore, if a 95 per cent confidence level is selected, the extreme 5 per cent of losses are excluded. This is an important weakness in a credit context, as it is precisely in these extreme circumstances that firms are most likely to fail.

Conditional Value at Risk (CVaR) is a measure initially used in the insurance industry for determining extreme returns (those beyond VaR). The metric has been shown by Pflug (2000) to be a coherent risk measure without VaR's undesirable properties. CVaR has been applied to portfolio-optimisation problems by Alexander and Baptista (2003), Alexander et al. (2003), Andersson et.al (2000), Birbil et al. (2009), Rockafellar and Uryasev (2002), Rockafellar et al. (2006), and Menoncin (2009) and Uryasev and Rockafellar (2000). CVaR has also been explored as a market- and credit-risk measure by Allen and Powell (2009a, 2009b), who found that CVaR yields results consistent to VaR when used to measure pre-GFC Australian industry risk rankings. Using CVaR, Powell and Allen (2009) also found that industries that had been risky before the GFC, from both a credit- and a market-risk perspective, were not the same industries that were risky during the GFC. CVaR studies in a credit context are still in their infancy, and aside from the studies by Allen and Powell there has been little application of CVaR in Australia.

As opposed to VaR, the Merton/KMV model uses Distance to Default (DD) and Probability of Default (PD) as measures of credit risk. Default is considered to be the point where a firm's liabilities exceed asset values. (These metrics are more fully explained in a later section of this paper). The model is termed a structural model, as DD depends on the structure of the firm's balance sheet as well as fluctuations in the market value of assets. Examples of studies using structural methodology for varying aspects of credit risk include predictive value and validation (Bharath & Shumway 2008; Stein 2007), fixed-income modelling (D'Vari, Yalamanchili & Bai 2003), and the effect of default risk on equity returns (Chan, Faff & Kofman 2008; Gharghori, Chan & Faff 2007; Vassalou & Xing 2002).

4. DATA AND METHODOLOGY

Data

Data is divided into two periods: pre-GFC and GFC. Our pre-GFC period includes the seven years from January 2000 to December 2006. This seven-year period aligns with Basel Accord advanced-model credit-risk requirements. Our GFC period includes January 2007 to June 2009. For our

Merton/KMV model, which requires equity prices, the study includes entities listed on the Australian Stock Exchange (ASX) All Ordinaries Index (All Ords) for which equity prices and Worldscope balance-sheet data are available in Datastream. Entities with less than 12 months' data in either of the two periods, or industries with fewer than five companies, are excluded. We consider this to be a fair representation of Australian listed entities, given that the All Ords includes more than 90 per cent of listed Australian companies by market capitalisation, and our data sample includes approximately 90 per cent of All Ords entities. The other models examined all require external ratings. For these models (Basel, Undiversified Transition and *i*Transition), we use all Australian entities with a Standard & Poor's or Moody's rating (not all companies have an external rating, and to ensure a reasonable number of companies are included in each industry, we exclude any industries with fewer than five companies; these are Automobiles and Components, Capital Goods, Commercial Services and Supplies, Food and Staples Retailing, Pharmaceuticals and Biotechnology, Retailing and Technology). Although this reduces the number industries, it nonetheless provides 14 industries for analysis using these models. For standardisation, all Moody's ratings are mapped to Standard & Poor's (Crosbie & Bohn 2003). Correlation (diversification) among assets in the portfolio is not calculated, as we are not calculating the risk measures for investment purposes, and do not need to show the effect of portfolio diversification. Industry risk measurement (VaR, CVaR, DD or CDD) for each model is calculated on each firm in each industry, rather than an industry index, with the industry portfolio simply showing the weighted average of these firms to allow comparison across industries.

Methodology Model 1: Structural Model

We use the Merton/KMV approach to estimating default, modifying the calculation to incorporate a CVaR component (which we term CPD, as the model uses probability of default rather than VaR). The structural-model point of default is where the firm's debt exceeds asset values. KMV (Crosbie & Bohn 2003), in modelling defaults using their extensive worldwide database of over 250,000 company-years of data and over 4,700 incidents of default, finds that in general firms do not default when asset values reach total liability book values. Many continue to trade and service their debts at this point, as the long-term nature of some of their liabilities provides some breathing space. KMV finds that the default point – the asset value at which the firm will default – generally lies somewhere between total liabilities and current, or short-term, liabilities (modelling evidence from their extensive database shows approximately halfway). Thus KMV uses current debt plus half of long-term debt as the default point. Distance to default (DD) and probability of default (PD) are measured as

$$DD = \frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}} \tag{1}$$

$$PD = N(-DD) \tag{2}$$

where

V = market value of firm's assets

F = face value of firm's debt (in line with KMV, this is defined as current liabilities plus one half of long-term debt)

μ = an estimate of the annual return (drift) of the firm's assets

N = cumulative standard normal distribution function.

Of all the well-known credit models, the Merton/KMV approach provides the strongest focus on the market, with fluctuations in the market value of assets forming a core component of the model. On the other hand, a comparison to the customer models in this study, which are based on external ratings incorporating a vigorous customer assessment, highlights the fact that the structural-model customer component is very narrow, focusing only on the distance between asset values and debt (solvency). In an Australian setting, the Australian Prudential Regulation Authority (APRA) website contains papers (Sy 2007, 2008), arguing that the Merton/KMV approach suffers from incomplete causality, especially in regard to serviceability: technical insolvency, as measured by the relationship between debt and equity, is not a sufficient condition for default of secured loans, as many technically insolvent entities continue to make debt repayments.

It should be noted that KMV finds that the PD values arising from the normal distribution are very small, and hence use their own extensive database of defaulting entities to derive an Estimated Default Frequency (EDF) from DD values, to which we do not have access. For this reason, we will report DD values only, as opposed to PD values. This has no impact on our industry rankings, as a riskier DD ranking also has a riskier PD ranking. First, we obtain daily equity returns for each entity, and calculate the standard deviation of the logarithm of price relatives. Following the estimation, iteration and convergence procedure outlined by Allen and Powell (2009a), Bharath and Shumway (2009) and KMV (2008) we obtain asset values and asset returns. These figures are then applied to the DD and PD calculations in Equations 1 and 2. We measure μ as the mean of the change in lnV as per Vassalou and Xing (2002). In accordance with KMV, debt is measured as current liabilities plus one half of long-term liabilities.

We define conditional distance to default (CDD) as being DD on the condition that standard deviation of asset returns exceeds standard deviation at the 95 per cent confidence level, i.e. the worst 5 per cent of asset returns. We term the standard deviation of the worst 5 per cent of returns for each period as CStdev, which we then substitute into Equation 1 to obtain a conditional DD:

$$CDD = \frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{CStdev_V \sqrt{T}} \tag{3}$$

Methodology Model 2: Basel Model

The Basel standardised model requires that 8 per cent of risk-weighted assets be held as capital for credit risk. Whilst the Basel model is used for calculating the capital requirements of financial firms, it is based on measuring the risk of the underlying customers, who come from a range of industries. We use our portfolio of all Australian rated entities to calculate capital requirements for each industry. Risk weightings used to calculate credit risk for corporate customers are as follows:

Rating	AAA to AA-	A+ to A-	BB+ to BB-	Below BB-	Unrated
Risk weighting	20%	50%	100%	150%	100%

Methodology Model 3: Undiversified Transition Model

This model is based on the probability (ρ) of a bank customer transitioning from one grade to another, as shown in the following BBB example:

BBB	ρ_{AAA}	ρ_{AA}	ρ_{A}	ρ_{BBB}	ρ_{BB}	ρ_{B}	$\rho_{CCC/C}$	ρ_{D}

External raters such as Moody's and Standard & Poor's (S&P) provide transition probabilities for each grading; we use the S&P (2008) global-transition probabilities. We exclude non-rated categories and adjust the remaining categories on a pro-rata basis, as is the practice of CreditMetrics (Gupton et al. 1997). The sum of all probabilities must equal 1.

We follow CreditMetrics methodology as described in the following paragraphs. The model obtains forward-zero curves for each rating category (based on risk-free rates) expected to exist in a year's time. Using the zero curves, the model calculates the market value (V) of the loan, including the coupon, at the one-year risk horizon. Effectively, this means estimating the change in credit spread that results from migration from one rating category to another, then calculating the present value of the loan at the new yield to estimate the new value. The following example values a five-year loan, paying a coupon of 6 per cent, where r = the risk-free rate (the rate on government bonds) and s = the spread between a government bond and corporate bonds of a particular category, say AA (Gupton et al. 1997).

$$V = 6 + \frac{6}{(1+r_1+s_1)} + \frac{6}{(1+r_2+s_2)^2} + \frac{6}{(1+r_2+s_2)^3} + \frac{106}{(1+r_2+s_2)^4} \qquad (4)$$

The above is calculated for each rating category (yields for government and corporate bonds can be obtained from RBA or other central bank websites). Probabilities in the transition table (in this case obtained from the S&P global transition table) are multiplied by V for each rating category to obtain a weighted probability. Based on the revised probability table, VaR is obtained by calculating the probability-weighted portfolio variance and standard deviation (σ), then calculating VaR using a normal distribution (for example 1.645σ for a 95 percent confidence level).

We extend this methodology (Gupton et al. 1997) to calculate CVaR by using the lowest 5 per cent of ratings for each industry; we call this 'Analytical CVaR'.

CreditMetrics (see also Allen & Powell 2009b) use Monte Carlo modelling as an alternate approach to estimating VaR. Transition probabilities and a normal distribution assumption are used to calculate asset thresholds (Z) for each rating category as follows:

$$Pr_{(Default)} = \Phi(Z_{Def}/\sigma)$$
$$Pr_{(CCC)} = \Phi(Z_{CCC}/\sigma) - \Phi(Z_{Def}/\sigma) \qquad (5)$$

and so on, where Φ denotes the cumulative normal distribution, and

$$Z_{Def} = \Phi^{-1}\sigma \qquad (6)$$

Scenarios of asset returns are generated using a normal distribution assumption. These returns are then mapped to ratings using the asset thresholds. A return falling between rating thresholds will correspond to the rating threshold immediately above it. In line with this methodology, we generate 20,000 returns for each customer from which a portfolio distribution and VaR are calculated. We extend this methodology (1999) to calculate CVaR by obtaining the worst 5 per cent of the 20,000 returns for each industry; we call this 'Monte Carlo CVaR.'

Methodology Model 4: *i*Transition Model

CreditPortfolioView, a variation on the undiversified transition model, incorporates an adjustment to transition probabilities based on industry and country factors calculated from macroeconomic variables. This model recognises that customers of equal credit rating may transition differently depending on their industry risk. A study by APRA (1999) showed that banks did not favour using macroeconomic factors in their modelling due to the complexities involved. Our own *i*Transition model (Allen & Powell 2009b) uses the same framework as CreditPortfolioView, but incorporates equity VaR instead of macroeconomic variables to derive industry adjustments. This is done by calculating market VaR for each industry, then calculating the relationship between market VaR and credit risk for each industry, using the Merton model to calculate the credit-risk component. These factors are used to adjust the model as follows, using a BBB-rated loan example:

BBB	ρ_{AAAi}	ρ_{AAi}	ρ_{Ai}	ρ_{BBBi}	ρ_{BBi}	ρ_{Bi}	$\rho_{CCC/Ci}$	ρ_{Di}

The incorporation of industry market factors into the *i*Transition model gives it a higher market focus than the Basel or undiversified Transition models. However, as external customer ratings are still entrenched in the *i*Transition model, it retains a greater balance between customers and markets than the heavily market-weighted structural model.

5. RESULTS

Structural Model Results

Table 1
DD and CDD Results – Structural Model

DD (measured by number of standard deviations) is calculated using Equation 1. CDD is based on the worst 5 per cent of asset returns and is calculated using Equation 3. Figures for GFC are based on daily returns for 2007 to mid-2009. Figures for pre-GFC incorporate seven years of data to 2006. A negative movement means a deterioration in DD or CDD during the GFC as compared to pre-GFC. Data is sorted in order of GFC CDD from lowest to highest risk.

	DD Pre-GFC	DD GFC	Movement	CDD Pre-GFC	CDD GFC	Movement
Healthcare Equipment & Services	8.86	10.66	1.79	5.86	3.11	-2.74
Food, Beverage & Tobacco	9.44	8.49	-0.95	5.06	2.72	-2.33
Utilities	13.93	8.64	-5.28	6.17	2.62	-3.55
Pharmaceuticals & Biotechnology	7.64	6.67	-0.97	4.54	2.14	-2.40
Telecommunication Services	9.40	7.07	-2.33	6.59	2.13	-4.46
Energy	9.52	6.50	-3.01	5.36	1.84	-3.54
Food & Staples Retailing	10.06	6.14	-3.92	5.33	1.82	-3.53
Media	9.97	5.62	-4.35	5.00	1.78	-3.25
Consumer Durables & Apparel	9.27	5.23	-4.04	5.16	1.61	-3.52
Technology	5.64	5.22	-0.42	3.84	1.58	-2.27
Commercial Services & Supplies	7.80	5.23	-2.57	4.53	1.48	-3.02
Retailing	7.12	4.40	-2.71	4.35	1.44	-2.89
Transportation	8.31	4.75	-3.56	4.31	1.41	-2.87
Metals & Mining	8.50	3.92	-4.59	5.86	1.12	-4.75
Real Estate	11.54	3.35	-8.19	6.26	0.93	-5.32
Capital Goods	8.49	3.07	-5.42	4.99	0.82	-4.17
Insurance	3.70	2.12	-1.59	3.38	0.60	-2.78
Banks	8.26	1.18	-7.07	5.19	0.39	-4.81
Automobiles & Components	5.80	1.09	-4.71	3.26	0.27	-2.99
Diversified Financials	11.65	0.59	-11.06	5.17	0.16	-5.01
All	8.54	4.37	-4.17	4.95	0.56	-4.39

Table 1 shows DD and CDD values; Table 2 gives their rankings. Real Estate, Diversified Financials and Banks show the greatest declines in CDD rankings.

The structural model essentially consists of two key components that influence DD: the capital of the borrower (a customer component) and asset-value fluctuations (a market component). These in turn are affected by share-price fluctuations. To illustrate the relative importance of the customer-versus-market component of our results, Table 3 shows the relative equity (capital) of each industry as a proxy for the customer component, and the CVaR of the equities as a proxy for the market component. To obtain CVaR, we measure the equity returns for each day and calculate the standard deviation of the price relatives logarithm for the worst 5 per cent of returns.

Table 2
DD and CDD Rankings – Structural Model

The table provides sector rankings for the outputs in Table 1. Sectors are ranked from 1 (lowest risk) to 20 (highest risk). Negative movement indicates deterioration in ranking. Positive movement does not mean that the DD or CDD necessarily improved, but that the ranking improved relative to other industries. Data is sorted in order of GFC CDD from lowest to highest risk.

	DD Pre-GFC	DD GFC	Movement	CDD Pre-GFC	CDD GFC	Movement
Healthcare Equipment & Services	10	1	9	4	1	3
Food, Beverage & Tobacco	7	3	4	11	2	9
Utilities	1	2	-1	3	3	0
Pharmaceuticals & Biotechnology	16	5	11	14	4	10
Telecommunication Services	8	4	4	1	5	-4
Energy	6	6	0	6	6	0
Food & Staples Retailing	4	7	-3	7	7	0
Media	5	8	-3	12	8	4
Consumer Durables & Apparel	9	10	-1	10	9	1
Technology	19	11	8	18	10	8
Commercial Services & Supplies	15	9	6	15	11	4
Retailing	17	13	4	16	12	4
Transportation	13	12	1	17	13	4
Metals & Mining	11	14	-3	5	14	-9
Real Estate	3	15	-12	2	15	-13
Capital Goods	12	16	-4	13	16	-3
Insurance	20	17	3	19	17	2
Banks	14	18	-4	8	18	-10
Automobiles & Components	18	19	-1	20	19	1
Diversified Financials	2	20	-18	9	20	-11

The market factor shown in Table 3 ranges from 0.5 to 1.7. The customer factor ranges from 0.8 to 4.1. The larger customer range is brought about by the financial sector (Banks, Insurance, and Diversified Financials). Excluding these gives a much narrower range.

Banks traditionally have lower equity structures than other industries, with loans primarily funded by deposits as opposed to equity. This means they have a lower distance to travel to default than other industries. The market-risk component as measured by CVaR in this instance is highest for Diversified Financials. Table 4 splits these into risk bands.

Table 3
Relative Market and Customer Risk

The table shows the relative risk for the market (CVaR), customer (capital) and CDD for the GFC period. The figures are calculated as industry risk/average portfolio risk. Thus, a value of 1 means that the industry risk is in line with the average overall portfolio risk, 2 means that the industry risk is double the average overall portfolio risk and 0.5 means the industry risk is half the average overall portfolio risk. Data is sorted in order of GFC CDD from lowest to highest risk.

	Market	Customer	CDD
Healthcare Equipment & Services	0.8	0.9	0.5
Food, Beverage & Tobacco	0.7	1.0	0.5
Utilities	0.7	1.2	0.6
Pharmaceuticals & Biotechnology	1.0	0.8	0.7
Telecommunication Services	0.5	1.0	0.7
Energy	1.3	0.8	0.8
Food & Staples Retailing	0.7	0.9	0.8
Media	0.9	0.9	0.9
Cons. Durables, Apparel, Services	0.8	0.8	0.9
Technology	1.2	0.8	0.9
Commercial Services & Supplies	1.1	0.9	1.0
Retailing	0.9	0.9	1.0
Transportation	1.0	1.1	1.0
Metals & Mining	1.3	0.8	1.4
Real Estate	1.3	1.0	1.6
Capital Goods	1.2	0.8	1.8
Insurance	0.9	2.2	2.5
Banks	0.7	4.1	3.9
Automobiles & Components	1.3	1.2	5.6
Diversified Financials	1.7	1.9	9.3

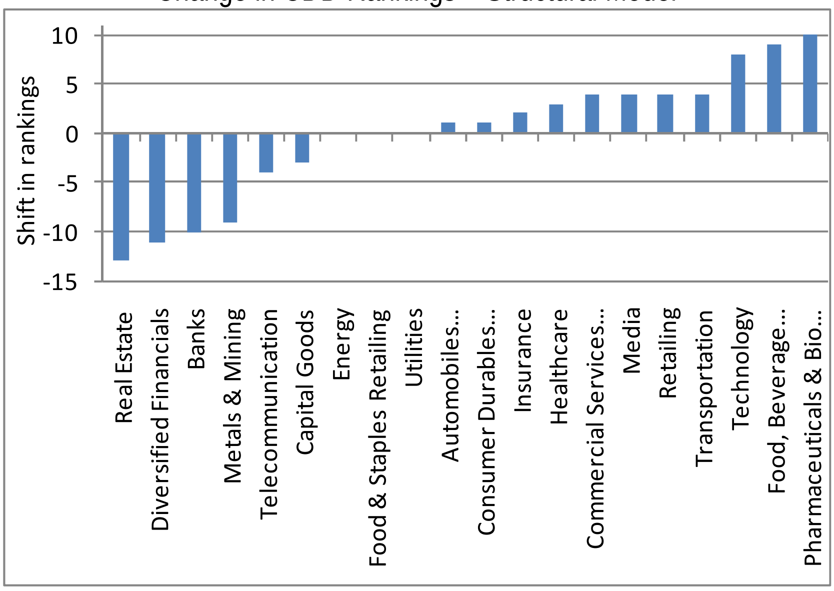
Table 4 clearly illustrates which component – customer or market – is driving the CDD, with different components driving different industries. High risk on both fronts, such as in Diversified Financials and Automobiles & Components, results in high overall high risk as measured by CDD. Whilst banks and insurance companies have lower market risk, the high capital risk component causes high CDD risk. Energy has high market risk but low customer risk, resulting in a medium-low CDD risk. Which component has the greatest influence on CDD? We use the Spearman rank correlation coefficient to measure correlation between market risk and CDD, and between customer risk and CDD. The result is the same for the data both before and during the GFC. Association between CDD rankings and market rankings are significant at the 95 per cent level, whereas association between customer rankings and CDD rankings is not. This indicates that the market measure has a greater influence on CDD rankings than the customer measure. Figure 1 shows change in CDD rankings from pre-GFC to GFC, as measured in Table 2. The largest deterioration in rankings is experienced by Real Estate, Diversified Financials and Banks. This is not surprising, given the problems experienced by the financial sector during the GFC.

Table 4
Risk Categories – Structural Model

The table shows the relative risk for the GFC period in categories of low (20th percentile), medium low (>20th to 40th percentile, medium (>40th to 60th percentile), medium-high (>60th to 80th percentile) and high (> 80th percentile). Data is sorted in order of GFC CDD from lowest to highest risk.

	Market	Customer	CDD
Healthcare Equipment & Services	Med-low	Med-low	Low
Food, Beverage & Tobacco	Low	Med-high	Low
Utilities	Low	Med-high	Low
Pharmaceuticals & Biotechnology	Med	Low	Low
Telecommunication Services	Low	Med	Med-low
Energy	High	Low	Med-low
Food & Staples Retailing	Low	med-low	Med-low
Media	Med	Med	med-low
Cons. Durables, Apparel, Services	Med-low	Low	Med
Technology	Med-high	Low	Med
Commercial Services & Supplies	Med-high	Med	Med
Retailing	Med	Med	Med
Transportation	Med	Med-high	Med-high
Metals & Mining	High	Med-low	Med-high
Real Estate	Med-high	Med-high	Med-high
Capital Goods	Med-high	Med-low	Med-high
Insurance	Med-low	High	High
Banks	Med-low	High	High
Automobiles & Components	High	High	High
Diversified Financials	High	High	High

Figure 1
Change in CDD Rankings – Structural Model



Prior to the financial crisis, Allen and Powell (2009a) found significant correlation between those industries that are risky from a market perspective (share-price volatility) and those that are risky from a credit perspective (PD as measured by the Merton model). The authors (Powell

& Allen 2009) also found that there continues to be a strong relationship (99 per cent confidence) between market- and credit-risk rankings during the GFC. However, they found no association between CPD industry rankings during the GFC and those pre-GFC, showing that relative risk between sectors changes with different economic conditions.

Basel Model Results

Table 5 shows ratings for all entities rated externally by S&P and Moody's, and the risk weightings that apply according to the Basel II Standardised model. The table shows that there are not a vast number of rating changes after the onset of the GFC. A bank holding this portfolio of assets would see its capital increase only marginally, from 3.08 per cent to 3.31 per cent; this indicates that according to the Basel model, there has been negligible change in credit risk since the onset of the GFC.

Table 5
Risk Weightings and Capital Requirements

Column 1 shows the external credit rating. Risk weightings in Column 2 reflect Basel requirements for corporate counterparties. Capital requirement is measured as 8 per cent of risk-weighted assets in line with Basel. This is shown as a percentage of total assets in the final row of the table.

Rating	Risk Weighting	Pre-GFC % of portfolio in this category	GFC % of portfolio in this category
AAA to AA-	20%	62.83%	59.86%
A+ to A-	50%	22.23%	21.56%
BB+ to BB-	100%	14.94%	18.56%
Below BB-	150%	0%	0.02%
Capital Required as % of Total Assets		3.08%	3.31%

We have not shown an industry split for this model, as it is based on external ratings and would therefore have the same relative industry risk as the undiversified transition model shown below. For example, an AA rating for a mining borrower carries the same capital requirement under the Basel standardised model as an AA rating for a retailer. The same applies to the undiversified transition model, where VaR for an AA retailer is the same as VaR for an AA miner. Whilst the two models have the same *relative* industry risk, it is still necessary to examine both models separately, as they have very different absolute outcomes (the Basel model being based on capital requirements and the undiversified transition model being the calculation of potential value at risk and conditional value at risk, which measures extreme risk). The Basel model has universal application, being used by more than 100 countries, including all G20 countries.

Undiversified Transition Matrix Results

Tables 6 and 7 show that whilst there has been an increase in overall default risk since the GFC, this increase is very small in comparison to that shown by the structural model. The simpler Analytical CVaR model of Powell and Allen shows very similar results to the more complex Monte Carlo modelling option.

Table 6
VaR and CVaR – Undiversified Transition Matrix Pre-GFC

The first three columns show daily VaR and CVaR figures for the undiversified transition model, with the final three columns showing rankings. A ranking of 1 represents the lowest risk and 14 the highest. Calculation of Analytical CVaR and Monte Carlo CVaR is as described earlier in this paper. Data has been sorted on Analytical CVaR from lowest to highest risk.

Industry	**95% VaR**	**CVaR Analytical**	**CVaR Monte Carlo**	**95% VaR**	**CVaR Analytical**	**CVaR Monte Carlo**
Banks	0.0145	0.0131	0.0135	1	1	1
Diversified Financials	0.0289	0.0669	0.0658	5	8	8
Energy	0.0506	0.0579	0.0598	8	7	7
Food, Beverage & Tobacco	0.0743	0.1787	0.1730	13	14	14
Healthcare	0.0929	0.1588	0.1629	14	13	13
Insurance	0.0207	0.0237	0.0232	3	4	4
Media	0.0533	0.0674	0.0722	10	9	10
Metals & Mining	0.0209	0.0212	0.0204	4	2	2
Other Consumer Discretionary	0.0739	0.1417	0.1412	12	12	12
Other Materials	0.0592	0.0685	0.0704	11	10	9
Real Estate	0.0328	0.0470	0.0454	6	6	5
Telecommunication Services	0.0206	0.0225	0.0222	2	3	3
Transportation	0.0512	0.0785	0.0805	9	11	11
Utilities	0.0354	0.0456	0.0459	7	5	6
Total	0.0242	0.0342	0.0343			

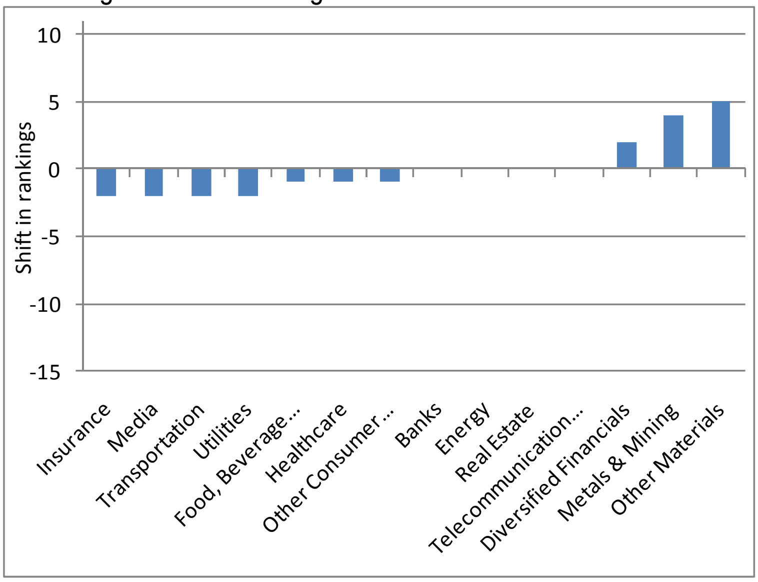
There is no major change in relative risk ratings between pre-GFC and GFC. Changes in ratings are not significant at the 95 per cent level of confidence using the Spearman rank correlation coefficient. Figure 2 shows a much flatter profile of CDD ranking shifts than those associated with the structural model in Figure 1. This is because the transition model, unlike the structural model, has not factored in the relative shifts in industry market asset values. Indeed, there is no relation between the industry shifts identified by the transition model and those identified by the structural model. For example, one of the greatest improvements shown in the transition model is in Metals and Mining; in contrast, the structural model shows significant deterioration in that sector. To give another example, the undiversified transition model shows Banks (no change) and Diversified Financials (improvement) to fare much better in terms of ranking shifts than does the the structural model, in which both show significant deterioration.

Table 7
VaR and CVaR Undiversified Transition Matrix GFC

The table shows the same items as Table 6, but for the GFC period rather than the pre-GFC. Data has been sorted on Analytical CVaR from lowest to highest risk.

Industry	95% Undiversified VaR	CVaR Analytical	CVaR Monte Carlo	95% Undiversified VaR	CVaR Analytical	CVaR Monte Carlo
Banks	0.0202	0.0253	0.0166	1	1	1
Insurance	0.0279	0.0350	0.0307	2	2	2
Telecommunication Services	0.0308	0.0386	0.0342	3	3	3
Real Estate	0.0361	0.0453	0.0484	4	4	5
Diversified Financials	0.0367	0.0460	0.0736	5	5	10
Utilities	0.0380	0.0476	0.0463	6	6	4
Metals & Mining	0.0454	0.0570	0.0516	7	7	6
Energy	0.0481	0.0602	0.0538	8	8	7
Transportation	0.0520	0.0651	0.0723	9	9	9
Media	0.0538	0.0674	0.0697	10	10	8
Other Consumer Discretionary	0.0647	0.0811	0.1180	11	11	11
Food, Beverage & Tobacco	0.0712	0.0892	0.1577	12	12	13
Healthcare	0.0743	0.0932	0.1242	13	13	12
Other Materials	0.0915	0.1147	0.1801	14	14	14
Total	0.0306	0.0396	0.0363			

Figure 2
Change in CDD Rankings – Undiversified Transition Model



*i*Transition Results

Table 8
VaR and CVaR – *i*Transition GFC

The first three columns show daily VaR and CVaR for the *i*Transition model, with the final three columns showing rankings. A ranking of 1 represents the lowest risk and 14 the highest. Calculation of Analytical CVaR and Monte Carlo CVaR are as described earlier in this study. Data has been sorted on Analytical CVaR from lowest to highest risk.

Industry	**95% Undiversified VaR**	**CVaR Analytical**	**CVaR Monte Carlo**	**95% Undiversified VaR**	**CVaR Analytical**	**CVaR Monte Carlo**
Energy	0.0647	0.0811	0.0898	1	1	1
Metals & Mining	0.0648	0.0812	0.0919	2	2	2
Transportation	0.0658	0.0825	0.1000	3	3	4
Media	0.0660	0.0828	0.0921	4	4	3
Utilities	0.0667	0.0837	0.1028	5	5	5
Real Estate	0.0677	0.0849	0.1046	6	6	6
Telecommunication Services	0.0682	0.0855	0.1087	7	7	7
Insurance	0.0712	0.0892	0.1171	8	8	9
Other Consumer Discretionary	0.0714	0.0896	0.1261	9	9	11
Diversified Financials	0.0734	0.0920	0.1232	10	10	10
Healthcare	0.0749	0.0940	0.1118	11	11	8
Banks	0.0801	0.1004	0.1408	12	12	12
Food, Beverage & Tobacco	0.0882	0.1106	0.1491	13	13	13
Other Materials	0.0950	0.1191	0.1514	14	14	14
Total	0.0762	0.0921	0.0955			

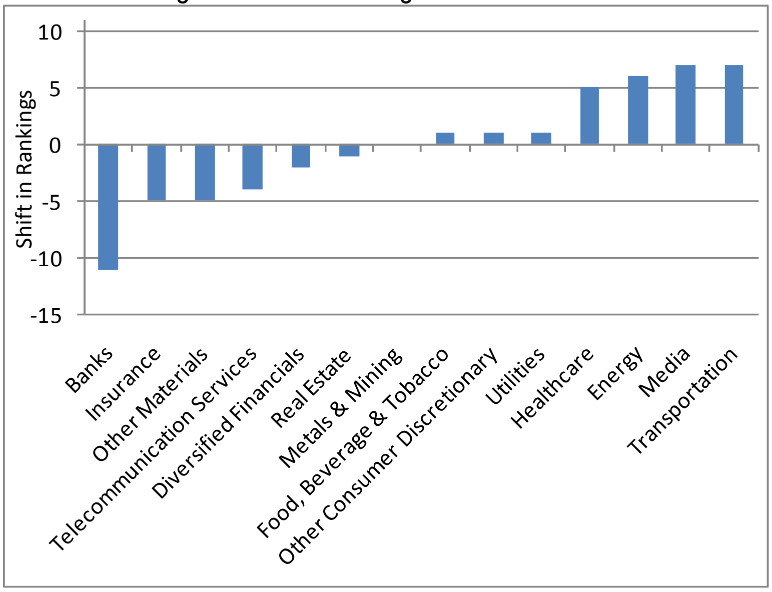
We use the same start point as for the undiversified model (i.e. pre-GFC position, as in Table 6). Table 8 shows the GFC position using *i*Transition methodology described earlier. *i*Transition shows a much greater increase in VaR (to 0.08) and CVaR (0.09) than the undiversified model (0.03 and 0.04, respectively). This shows that the industry profile affects the results. As there is a large component of financial-sector assets among rated entities, and these sectors have experienced a large reduction in the market value of their assets, the increase in VaR and CVaR is expected, and the model is doing its job in identifying increased credit risk.

There is association between VaR (and CVaR) rankings before and during the GFC using the undiversified transition matrix at a 99 per cent confidence level. There is no association between VaR (and CVaR) rankings before and during the GFC using the *i*Transition model at a 95 per cent confidence level.

Figure 3 shows similar deterioration in rankings to those identified by the structural model for the financial industry (Banks, Insurance, Diversified Financials and Real Estate). The shifts in rankings for *i*Transition (-11 to +7) are not as pronounced as for the structural model (-13 to +10), but are not nearly as flat as the undiversified transition model.

Figure 3

Change in CVaR Rankings – *i*Transition Model



Overall Summary of Results

The summary in Table 9 highlights the vast difference in outcomes between the customer- and market-based models.

The customer-based Basel and undiversified transition models show very little change in credit risk with only nominal changes in capital requirements (Basel model) and VaR/CVaR (undiversified transition model). There is no significant change in industry rankings. The market-based structural model shows large increases in DD and CDD, and the market-based *i*Transition model shows much higher increases in credit risk than the undiversified transition model.

The customer-based models show no significant shift in relative industry rankings. There is correlation between those industries that were risky prior to the GFC and those industries that are risky during the GFC. The market-based models show that those industries that were risky prior to the GFC are not the same as those that are most risky during the GFC.

How do these outcomes compare with the actual credit problems experienced by Australian banks? These banks are generally considered to have performed much better during the GFC than their global counterparts: the sector showed continued profitability and adequate capitalisation, and the four major banks retained their AA ratings. Nonetheless, an examination of aggregated impaired assets and provisions for Australian banks shows that impaired assets increased from 0.19 per cent to 0.95 per cent (fivefold) and provisions from 0.38 per cent to 0.69 per cent (nearly double) over the 24 months ended March 2009. This shows that credit risk has not stayed the same, a conclusion supported by a drop in bank share prices of 58 per cent during the GFC. Clearly the customer-only models are not reflecting this. The (approximate) trebling in VaR and CVaR estimates given by the *i*Transition model seems reasonably consistent with the increase in provisions and impaired assets of the banks. The structural model also highlights an increase in risk, although in line with KMV observations. We note that whilst DD may be accurately reflected, PD values derived from the DD using a normal distribution are questionable (converting DD to PD shows almost no risk before or after the GFC, which is clearly understated, whereas CPD is 29 per cent during the GFC, which appears highly overstated).

Table 9
Summary of Outcomes

The table provides a summary of the extent of changes in credit-risk measurements of Australian banks, as presented in detail on pages 14-23. A * indicates significance at the 95 per cent level and ** significance at the 99 per cent level.

Model	Customer- or market-based	Indicated change in credit risk	Extent of change	Significance of change in industry rankings
Basel	Customer	Very small	Increase in capital requirement from 3.08% to 3.31%	-
Undiversified transition	Customer	Very small	Increase in VaR from 0.0242 to 0.0306 and CVaR from 0.0342 to 0.0396	-
iTransition	Market (balanced)	Large	Increase in VaR from 0.0242 to 0.0762 and CVaR from 0.0342 to 0.0921	*
Structural	Market	Large	Reduction in DD from 8.54 to 4.37 and CDD from 4.95 to 0.56	**

6. CONCLUSIONS

The models investigated produced very different results. Customer-based models, including the Basel model and the undiversified transition model, showed very little change in overall credit risk or industry credit risk with the advent of the GFC. Market-based models showed a significant increase in risk during the GFC as compared to prior years, particularly using CVaR (or CDD), and also showed shifts in relative risk between industries. The customer-based models seem not to adequately recognise the fluctuations in the market value of assets and how these can differ among industries, whereas the market-based models can recognise them.

Overall, the increased risk shown by the market-only models is far more consistent with banks' actual increases in impaired assets and provisions (as discussed above) than the no-change position shown by the customer-only models. Customer-only models tend to be static, as they measure credit risk at a point in time and review ratings only periodically (often annually). Output from models that incorporate asset-value fluctuations can be updated regularly, even daily if required. This is important to banks, as these values provide early warning of deteriorating credit risk.

Analysis of individual customer circumstances is, of course, essential to understanding credit risk; we also note that PDs can be understated or overstated by the heavily market-weighted structural model, whereas this problem is not evident in the more balanced customer-market *i*Transition model. We conclude that analysis of both customers and markets is important to credit-risk measurement, and a two-factor market-customer approach is recommended. The customer component allows banks to measure and provide for individual customer circumstances, and the market component gives banks a means of early risk detection and lets them measure and provide for fluctuating economic circumstances. As discussed in the contribution and benefits section of this paper, this is essential so that banks are not left scrambling for capital in downturns.

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